

*EFFECTS OF RESPONSE DISPARITY ON
STIMULUS AND REINFORCER CONTROL IN
HUMAN DETECTION TASKS*

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In two detection experiments, university students reported whether the second of two sequentially presented tones was longer or shorter than the first by responding to stimuli presented on a touch screen. Stimulus disparity and response disparity were manipulated to compare their effects on measures of discrimination and response bias when the reinforcement ratio for correct responses was asymmetric. Choice stimuli consisted of squares filled with different pixel densities. Response disparity was manipulated by varying the difference in density between the two choice stimuli. In both experiments, decreasing stimulus disparity reduced discrimination but had no consistent effect on bias. Decreasing response disparity also reduced discrimination in both experiments, and often reduced estimates of bias. The effects of response disparity on bias were most clear in Experiment 2, in which a greater overall level of response disparity was arranged. The data show that, like corresponding research with pigeons, detection performance of human subjects can be conceptualized as discriminated operants.

Key words: detection, stimulus control, reinforcer control, discrimination, response bias, touch screen, humans

Organisms are continuously faced with situations that require a choice. Frequently, the choice involves distinguishing the environmental state and then making the response appropriate to that situation. Foraging animals, for example, must determine if a given patch contains prey or is empty, and stay or move to another patch as appropriate (e.g., Voss, McCarthy, & Davison, 1993). Decisions with two stimulus conditions (e.g., “prey” or “no prey”) and two responses (e.g., “stay” or “move”) are frequently referred to as detection tasks.

Detection theory (e.g., Green & Swets, 1966) had its origin in engineering and psychophysics, but has become a popular way to measure performance in detection tasks in a variety of settings (Alsop, 1998; Swets, 1988). In broad terms, detection theory can be applied to any situation that requires a discrim-

ination between two stimulus conditions (S_1 and S_2) that is reported by making one of two possible responses (B_1 or B_2). In applied settings, this decision process has been investigated in quality control (e.g., Mason & Redmon, 1992), medical decision making (e.g., Daubs, 1983; Loke, 1989), and a variety of other diagnostic situations (Swets, 1986, 1988). In experimental psychology this sort of task has been important in psychophysics, and has also been used in many other fields, such as recognition memory (e.g., Snodgrass & Corwin, 1988) and animal studies of stimulus and reinforcer control (e.g., Blough & Blough, 1977; Davison & McCarthy, 1988; Davison & Nevin, 1999).

The behavioral approach to analyzing these tasks treats performance as a series of discriminations (Alsop, 1998; Davison & Nevin, 1999). To perform the task successfully, the subject must discriminate between the two stimulus conditions and between the two response alternatives. If the stimuli are not easily discriminated, the subject might occasionally identify S_1 as S_2 (or S_2 as S_1) and make the corresponding, but incorrect, response. Similarly, if the response alternatives are not easily discriminated, then incorrect responding is likely regardless of the ease of the sample stimulus discrimination (Godfrey & Davison, 1998; Nevin, Cate, & Alsop, 1993). In either of these situations accuracy, or dis-

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crimination, will be reduced relative to conditions with easily discriminable stimuli and responses. The ability to discriminate the consequences of a response might also influence accuracy (Davison & Nevin, 1999; Nevin et al., 1993). For example, if the consequences of correct and incorrect responses are not discriminably different, then discriminative responding is not required for the same outcomes to be achieved.

A second aspect of performance in these tasks concerns biases for one or the other of the response alternatives that occur independently of the sample stimuli. These response biases are thought to be governed by reinforcement variables (McCarthy & Davison, 1981), with responses tending toward the alternative that results in the more frequent, larger, or less delayed reinforcement. The extent of these biases can be influenced by the extent to which the stimuli, responses, and consequences are distinguishable (e.g., Davison & Nevin, 1999).

A great deal of research has investigated the effects of changes in stimulus disparity on performance with both human and nonhuman animal subjects. In general, decreasing the physical disparity of the stimuli decreases accuracy (e.g., Alsop & Davison, 1991; Tanner & Swets, 1954). Few studies, however, have investigated the influence of systematically varying the disparity of response alternatives. Two recent studies with nonhuman animals (Godfrey & Davison, 1998; Nevin et al., 1993) have specifically addressed this issue. Nevin et al. trained pigeons to respond differentially to high-luminance (S_1) and low-luminance (S_2) stimulus presentations. Responses were distinguished by their latency, with relatively short-latency responses being correct following S_1 presentations and relatively long-latency responses being correct following S_2 presentations. Stimulus disparity was manipulated by varying the difference in luminance between the two stimuli, providing a large-difference condition and a small-difference condition. Response disparity was also manipulated by varying the latency criteria denoting B_1 and B_2 responses to provide large- and small-difference conditions. Accuracy was highest when both stimulus and response differences were large. Decreasing the disparity of either the stimuli or the responses reduced accuracy, suggesting a functional equivalence of the two

manipulations. Sensitivity to changes in the relative frequency of reinforcement, estimated by fits to the data of the Davison and Tustin (1978) model of detection performance (described below), was higher overall in conditions with a small stimulus disparity for both large and small response disparities. Within each stimulus-disparity condition, sensitivity to reinforcement was highest when the response disparity was large. In summary, sensitivity to reinforcement increased when the stimulus disparity was made smaller and decreased when response disparity was made smaller.

Recent behavioral models of detection performance (e.g., Alsop & Davison, 1991; Davison & Nevin, 1999) have been developed in an attempt to account for these sorts of interactions between stimulus and response disparity, and measures of discrimination and bias. These models provide two parameters that are designed to measure independently the discriminability of the stimulus–response relation and the response–reinforcer relation implicit in these tasks. Stimulus discrimination should be influenced by stimulus and response disparity, but should be unaffected by changes in reinforcement. Response–reinforcer discrimination, which replaces the sensitivity-to-reinforcement parameter of the Davison and Tustin (1978) model, should be influenced by response disparity and the discrimination of consequences, but should be unaffected by changes in stimulus disparity. In addition, these models suggest that the biasing effects of reinforcement will become more pronounced as stimuli become less discriminable. A second prediction is that increased confusability between responses will reduce reinforcer-based bias as the contingency between responses and their consequences becomes more ambiguous.

Nevin et al. (1993) reanalyzed their data using the Alsop–Davison model (Alsop, 1991; Alsop & Davison, 1991; Davison, 1991; Davison & Nevin, 1999) and reported that estimates of stimulus discrimination depended on differences in sample stimuli, and that estimates of response–reinforcer discrimination depended on the degree of response disparity. However, in this analysis stimulus discrimination also changed as a function of response disparity, and response–reinforcer discrimination was also influenced by changes in stimulus disparity. The presence of this

interaction raises difficulties for behavioral models of detection, because measures of stimulus discrimination and response–reinforcer discrimination should be independent under these conditions.

Godfrey and Davison (1998) replicated the Nevin et al. (1993) study to address these issues. They were concerned that the latency-based definition of responses in the Nevin et al. study might systematically bias performance. In general, pigeons have a tendency to respond quickly (e.g., Blough, 1978). A bias of this type might influence parameter estimates from the Alsop–Davison model. To overcome this, Godfrey and Davison used rectangular stimuli filled with different pixel densities for both the sample stimuli and the choice stimuli. In each condition, stimuli were arranged so that one sample stimulus contained more pixels than the other (S_1 and S_2 , respectively), except for a condition in which both stimuli had the same pixel density. Choice stimuli were also arranged so that one stimulus contained more pixels than the other. Pigeons' responses were occasionally reinforced for matching the relative density of the choice stimuli to the relative density of the sample stimuli. For example, given a presentation of the sample stimulus with the greatest pixel density, a correct response would be to peck the key signaled by the choice stimulus with the greatest pixel density. Both sample-stimulus and choice-stimulus disparity were parametrically varied across several levels.

Godfrey and Davison (1998) reported that their data supported the predictions of the Alsop–Davison model in 39 of 45 pairwise comparisons. Decreasing sample-stimulus disparity tended to reduce stimulus discrimination, and decreasing choice-stimulus disparity tended to reduce estimates of response–reinforcer discrimination. These data supported the independence of the two discrimination parameters of the Alsop–Davison model.

Both Godfrey and Davison (1998) and Nevin et al. (1993) demonstrated that confusability between response alternatives has effects on accuracy similar to those seen when stimulus disparity is varied; that is, reducing either stimulus or response disparity decreased estimates of accuracy. Furthermore, response-disparity manipulations affected the measured response bias induced by any re-

inforcement contingencies present in an environment. Together, these findings demonstrate that performance in detection procedures is jointly determined by discriminations among the stimuli, the responses, and the outcomes. In this sense, detection tasks can be viewed as a discrimination between two *discriminated operants* (Skinner, 1969). The discriminated operant describes the simplest chain of events that define a behavior: a stimulus (S), a response (B), and a consequence or reinforcer (R). Detection tasks comprise two discriminated operants in the sense that $S_1 \rightarrow B_1 \rightarrow R_1$ and $S_2 \rightarrow B_2 \rightarrow R_2$ (Davison & Nevin, 1999; Nevin et al., 1993).

The finding that response disparity influences accuracy and bias (Godfrey & Davison, 1998; Nevin et al., 1993) has implications for human performance in many decision-making situations. It suggests that accuracy and sensitivity to outcomes in human decision making would be compromised if the response alternatives are not clearly defined. Clear response alternatives would therefore be desirable not only in formal diagnostic or quality control settings but also in more everyday contexts such as teaching children road safety or to behave appropriately in potentially dangerous situations (see, e.g., Alsop, 1998). However, the present authors are unaware of any studies that have systematically investigated the influence of response disparity in human decision making. The present research, then, was designed to investigate the influence of response disparity on human detection performance.

Two discrete-trials experiments required participants to determine whether the second of two sequentially presented tones was longer or shorter than the tone immediately preceding it, and to report this decision by responding to one of two simultaneously presented choice stimuli. Response disparity was manipulated by varying the physical similarity of the choice stimuli. Stimulus disparity was manipulated independently of response disparity by varying the difference in duration between the tones comprising a stimulus presentation. In addition, differential frequencies of reinforcement, in the form of points and correct feedback, were arranged in each experiment so that one group of participants received more feedback for correct

Table 1

Characteristics of sample stimuli and choice stimuli for each level for stimulus and response disparity in Experiments 1 and 2. Sample stimulus values give the duration of the short and long tones used to create S_1 (short/long) and S_2 (long/short) presentations. Choice stimulus values give the number of dots present in B_1 (more dots) and B_2 (fewer dots) choice stimuli.

Experiment	Sample stimuli		Choice stimuli	
	Disparity	Values	Disparity	Values
1	Small	525 vs. 475 ms	Small	92 vs. 88 dots
	Large	550 vs. 450 ms	Medium	94 vs. 86 dots
			Large	96 vs. 84 dots
2	Small	525 vs. 475 ms	Small	96 vs. 84 dots
	Large	550 vs. 450 ms	Medium	98 vs. 82 dots
			Large	100 vs. 80 dots

B_1 responses and a second group received more feedback for correct B_2 responses. This allowed the influence of stimulus- and response-disparity manipulations on reinforcer-based bias to be assessed in tandem with their influence on accuracy. This design is analogous to the procedures employed by Nevin et al. (1993) and Godfrey and Davison (1998), allowing comparison of the current research with humans to that previously conducted with pigeons.

EXPERIMENT 1

METHOD

Participants

Twelve undergraduate psychology students (7 female and 5 male) participated for partial course credit. Their ages ranged from 18 to 23 years, with an average age of 19.3 years.

Apparatus

An IBM®-compatible 486 personal computer, equipped with a 16-bit soundcard and a Microtouch® touch screen that displayed 256 colors with a resolution of 1,024 by 768 pixels, presented all stimuli and recorded responses. The touch screen had a visible area of 28 cm by 20.5 cm and was recessed into a table and tilted towards the participant at an angle of approximately 22°. This was arranged to reduce the fatigue caused by repetitive responding to an upright screen. The table extended 37 cm from the bottom edge of the touch screen, providing a surface for participants to rest their arms between responses. Tone stimuli were presented through headphones. Software for generat-

ing stimuli and controlling experimental events was written by the authors using Turbo Pascal 6®. Millisecond accuracy for timing routines was achieved using the procedures developed by Bovens and Brysbaert (1990).

Tone stimuli were generated by the computer's soundcard and consisted of 560-Hz sine waves of varying duration. A long tone and a short tone were defined for the two stimulus-disparity conditions. A stimulus presentation consisted of a sequential presentation of the long and short tones, separated by an interstimulus interval of 750 ms. Each stimulus type was defined by the order in which the short and long tones were presented. An S_1 presentation was defined as a short tone followed by a long tone, with the reverse order defining an S_2 presentation. Stimuli were arranged in this manner to avoid the subjective shortening effect demonstrated by human participants when judging duration of tones separated temporally from a reference tone (Wearden & Ferrara, 1993). Durations for long and short tones for the two stimulus-disparity conditions are listed in Table 1. For the large stimulus-disparity condition, a long tone had a duration of 550 ms, and a short tone had a 450-ms duration. These durations were 525 ms and 475 ms, respectively, for the small stimulus-disparity condition. Following a stimulus presentation, subjects were required to make a response to one of two simultaneously presented choice stimuli. Each choice stimulus was defined by a 227 pixel by 227 pixel area. These areas were not precisely square due to the aspect ratio of the screen. Due to some undetected compression on the right side of the screen, the left choice stimulus measured approximately 57 mm by 55

mm and the right stimulus measured approximately 55 mm by 55 mm. A distance of 28 mm separated the two adjacent choice stimuli, which were arranged to be equidistant from all sides of the screen.

The two different types of choice stimuli (B_1 and B_2) were constructed by generating a 14 by 14 array for each stimulus and filling a given number of spaces in the array with filled 3 by 3 pixel squares, referred to as dots. On the screen, these dots were approximately 1 mm square. Adjacent dots were separated by 13 pixels, a distance on the screen of approximately 4 mm.

B_1 and B_2 choice stimuli were differentiated by the number of dots present in the square. In each choice pair, the stimulus containing the most dots (labeled the "more dots" response in instructions) was defined as B_1 , and the stimulus with the fewest dots (labeled the "less dots" response in instructions) was defined as B_2 . The number of dots defining each choice stimulus for the three response-disparity conditions are presented in Table 1. In the large response-disparity condition, for example, a B_1 choice stimulus contained 96 dots and a B_2 stimulus contained 84 dots. The location of the B_1 and B_2 choice stimuli on a given trial was selected randomly and without replacement from a list, so that across trials the two types of choice stimuli occurred with equal frequency on the left and right sides of the screen.

Procedure

On arrival at the laboratory, each participant was assigned to a reinforcement condition, with an effort made to keep the ratio of male to female participants approximately equal within conditions. Each participant then received the following instructions: "You will be presented with a series of trials. Each trial will begin with a warning signal in the middle of the screen." Each participant was instructed to press any key on the computer keyboard to view an example of the warning signal, which consisted of a small plus sign presented in the center of the screen.

"Immediately after the warning signal you will hear two tones, presented one after the other. The second tone will either be SHORTER or LONGER than the first. Following the tones, you will see two patterns (like

this)." An example of the choice phase of the trial was then presented. This consisted of presentation of a B_1 choice stimulus on the left side of the screen and a B_2 choice stimulus on the right side of the screen. The number of dots in the example patterns was chosen from the response-disparity values for the condition the participant was being exposed to in the current session.

"When the second tone is LONGER press the pattern with MORE dots. Here, the left pattern has MORE dots (press the MORE dots pattern now). When the second tone is SHORTER, press the pattern with LESS dots. Here, the right pattern has LESS dots (press the LESS dots pattern now)." Participants were then presented with information about consequences.

"Sometimes you will be told you are correct and five points are added to your score. This looks like this (press any key)." A response to the computer keyboard resulted in presentation of a reinforcer. This consisted of a brief presentation of a tone and the words "Correct! You have won five points" superimposed over a pattern of pixels presented in pseudorandom positions and colors.

"Sometimes you are told nothing. You could be right or wrong. You start with 100 points. Earn as many points as you can. Remember, when the second tone is SHORTER, press the LESS dots pattern and when the second tone is LONGER, press the MORE dots pattern. Please respond as quickly and accurately as you can. If you take too long, you will be told you are TOO SLOW and the next trial will begin. Press any key to begin the first block of trials."

A response to any key on the computer keyboard initiated the first trial. Each trial consisted of a warning signal, a tone-pair presentation and, immediately following the offset of the second tone, simultaneous presentation of the choice stimuli. If a reinforcer was scheduled, a correct response resulted in a 1-s presentation of the reinforcer followed by a 1-s period in which no stimuli appeared on screen (blackout) or a 1.5-s blackout if no reinforcer was scheduled. Incorrect responses resulted in 1.5 s of blackout. If a response did not occur within 2.5 s of response presentation, the trial ended with the words "TOO SLOW!" presented on the screen for 800 ms and a 700-ms blackout before the beginning

of the next trial. The time limit on responding was enforced to encourage attention to the task.

Following the completion of a block of 72 trials, the computer screen displayed a message informing the participant that the block had ended and the number of points earned so far in the current session. Participants initiated the next block with a response to the keyboard. There was no restriction placed on the interval between blocks, and participants were informed verbally to use this period to rest and make themselves comfortable before the next block of trials. Participants typically initiated the next block within 60 s of completion of the preceding block of trials. Sessions were usually completed within 40 to 45 min. At the completion of each session participants were thanked for their participation, and they were fully debriefed following completion of their third and final session.

Three levels of response disparity were created by manipulating the difference in the number of dots in the choice stimuli. Each participant experienced a different level of response disparity in each of the three sessions. A session consisted of 432 trials, divided into six blocks of 72 trials. Two levels of stimulus disparity were created by manipulating the difference in duration between the long and short tones. Stimulus disparity was manipulated within sessions, so that the first three blocks and the remaining three blocks of trials presented different levels of stimulus disparity. For example, a given session might consist of three blocks at the large stimulus-disparity level followed by three blocks at the small stimulus-disparity level. The order of presentation of the stimulus-disparity levels was counterbalanced across sessions and participants. The order of presentation of the different levels of response disparity was also counterbalanced across participants, with each session separated by a minimum of 24 hr.

The participants experienced different relative frequencies of reinforcement for the two types of correct responses. For 6 participants, correct B_1 responses were reinforced five times more frequently than correct B_2 responses (a 5:1 reinforcer ratio). This was arranged using a controlled-reinforcement procedure (McCarthy & Davison, 1979; Stubbs & Pliskoff, 1969) to ensure that the obtained re-

inforcer ratio closely matched the arranged ratio. At the beginning of each session and following each reinforcer delivery, the computer selected the next trial type (either S_1 or S_2) to be reinforced. This was selected randomly and without replacement from an array, which was constrained so that S_1 trials were selected for reinforcement five times more frequently than S_2 trials. Once a reinforcer was scheduled, no other reinforcers were arranged until the currently scheduled reinforcer was delivered. The remaining 6 participants experienced a 1:5 reinforcer ratio; that is, correct B_2 responses were reinforced five times more frequently than correct B_1 responses. The reinforcer presentations were arranged using the same controlled-reinforcer procedure. The points earned from reinforcer presentations were not exchangeable for any other reward (e.g., money or additional course credit).

RESULTS AND DISCUSSION

The number of B_1 and B_2 responses following each stimulus type were recorded, as were the number of reinforcers received for the two types of responses. The controlled-reinforcement procedure ensured that the log obtained reinforcer distribution (average = 0.72) was similar to the log arranged distribution (0.70) (see Appendix A). Responses from the first block of trials at each level of stimulus disparity (i.e., the first and fourth blocks from each session) were removed from the analyses. This gave participants time to adjust to the level of stimulus disparity in effect for that part of the session. Stability was assessed by comparing estimates of discrimination and response bias (see below) from each of the remaining two blocks of trials at each level of stimulus disparity. Wilcoxon matched-pairs signed-ranks tests (Siegel, 1956) failed to find reliable differences between summary measures from these two blocks for either the 5:1 or 1:5 reinforcer-ratio groups. Subsequent analyses were therefore conducted using the collapsed data from these two blocks of trials (Appendix A).

Performance was evaluated using the Davison and Tustin (1978) behavioral model of signal detection. This model, based on Baum's (1974) generalized matching law, asserts that performance in detection tasks is jointly determined by stimulus and reinforcer parameters (see Davison & McCarthy, 1988,

for review). A point estimate of discrimination ($\log d$) that is independent of reinforcer manipulations is calculated by taking half the log ratio of correct to incorrect responses; that is,

$$\log d = 0.5 \log \left(\frac{B_{11} \cdot B_{22}}{B_{12} \cdot B_{21}} \right), \quad (1)$$

where B_{11} denotes the number of correct B_1 responses following S_1 presentations, and B_{22} denotes the number of correct B_2 responses following S_2 presentations. B_{12} and B_{21} denote the number of incorrect responses following S_1 and S_2 , respectively. The parameter $\log d$ measures the tendency to make the correct response in the presence of each stimulus.

Similarly, response bias can be estimated by taking half the log ratio of B_1 to B_2 responses; that is,

$$\log b = 0.5 \log \left(\frac{B_{11} \cdot B_{21}}{B_{12} \cdot B_{22}} \right), \quad (2)$$

with notation as in Equation 1. Estimates of $\log b$ measure the combined effects of reinforcer and inherent biases. Positive estimates of $\log b$ reflect a preference for B_1 responding, whereas negative estimates reflect a preference for B_2 responding. Point estimates of discrimination and bias were calculated for each participant in each condition using Equations 1 and 2. Responses that occurred faster than 100 ms were regarded as false starts, and were removed from the analyses. These were extremely uncommon. One participant emitted a higher number of these responses than other participants in two conditions, but these were small proportions of the trials (0.09 and 0.08). The estimates of discrimination from these sessions were consistent with the overall pattern of performance for this and other participants. Trials that terminated without a response after 2,500 ms had elapsed were also infrequent, and accounted for less than 1% of the total trials.

Discrimination

Figure 1 shows plots of estimates of $\log d$ for each participant as a function of response disparity for large and small stimulus disparities. In general, discrimination decreased as a function of response disparity for both stim-

ulus-disparity conditions. When the stimulus disparity was large, 4 participants in the 5:1 group and 5 participants in the 1:5 group showed monotonically decreasing estimates of $\log d$ as response disparity decreased. When the stimulus disparity was small, 4 participants in the 5:1 group showed monotonically decreasing estimates of $\log d$. For the 1:5 group, although only 2 participants showed monotonic trends, a further 2 participants provided equal estimates of discrimination for the medium and small levels of response disparity and a higher estimate of discrimination when response disparity was large. These relations were evaluated by conducting a nonparametric trend analysis (Ferguson, 1965). This analysis ranks and weights the ordinal relation of the scores across conditions for each individual participant to determine monotonicity. As mentioned above, because there was no systematic difference between the performance of the 5:1 and 1:5 groups, these analyses were carried out using the combined data from both groups. All reported trends are directional tests. Monotonically decreasing trends were present for both the large stimulus-disparity condition ($\Sigma S = 30$, $z = 4.37$, $p < .05$) and the small stimulus-disparity condition ($\Sigma S = 22$, $z = 3.24$, $p < .05$).

The influence of stimulus disparity on discrimination was evaluated by comparing point estimates of discrimination from the large stimulus-disparity condition to those from the small stimulus-disparity condition at each level of response disparity. Wilcoxon matched-pairs signed-ranks tests revealed that when the stimulus disparity was large, accuracy was higher in the large response-disparity condition ($T = 2$, $p < .05$) and in the medium response-disparity condition ($T = 3$, $p < .05$). There was no difference between estimates of $\log d$ between large and small stimulus-disparity conditions when the response disparity was small ($T = 17$, $p > .05$).

Bias

Figure 2 plots estimates of $\log b$ as a function of response disparity for each stimulus-disparity condition. If behavior is biased by the reinforcer distribution, estimates of $\log b$ should be positive for the 5:1 group and negative for the 1:5 group. Surprisingly, the $\log b$ estimates obtained (Figure 2) suggest an overall lack of bias for the most reinforced

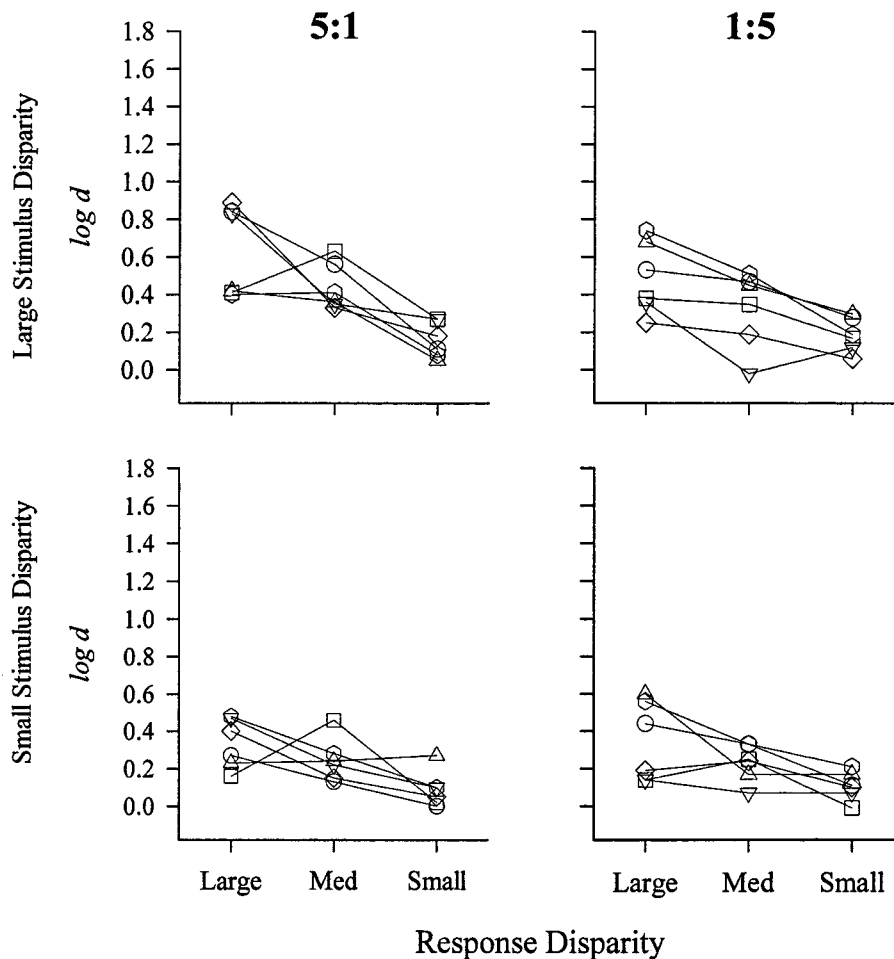


Fig. 1. Point estimates of discrimination ($\log d$) for each participant as a function of response disparity for the large stimulus-disparity condition (upper panels) and the small stimulus-disparity condition (lower panels) of Experiment 1. Estimates from the 5:1 and 1:5 reinforcer-ratio conditions are plotted in the left and right panels, respectively.

alternative. For the 5:1 group, estimates of bias were greater than 0 for 9 of the 18 cases when stimulus disparity was large and were greater than 0 for 10 cases when the stimulus disparity was small. Estimates of bias from the 1:5 group were below 0 in 14 of 18 cases for both stimulus disparities. This suggests that biases were generally in the direction predicted by the reinforcement ratio for the 1:5 group. However, the magnitude of the biases was small, with values of $\log b$ close to 0 in most cases, despite the presence of an unequal reinforcer distribution. A second feature of the data, probably an artifact of the first, is the lack of change in estimates of bias with changes in stimulus and response disparity. Although bias estimates are slightly

larger in some cases when response disparity is large, there is little evidence for biases being influenced systematically by response disparity.

The lack of an effect of the reinforcer-ratio manipulation is problematic, and is not predicted on the basis of prior research. A large body of literature supports the use of differential frequencies of reinforcement as a biasing factor with nonhuman animal subjects (for review, see Davison & McCarthy, 1988; Davison & Nevin, 1999). Procedures arranged in similar ways and using the same reinforcer as the current experiment have also demonstrated the efficacy of reinforcer frequency manipulations as a biasing factor with human participants (Al-

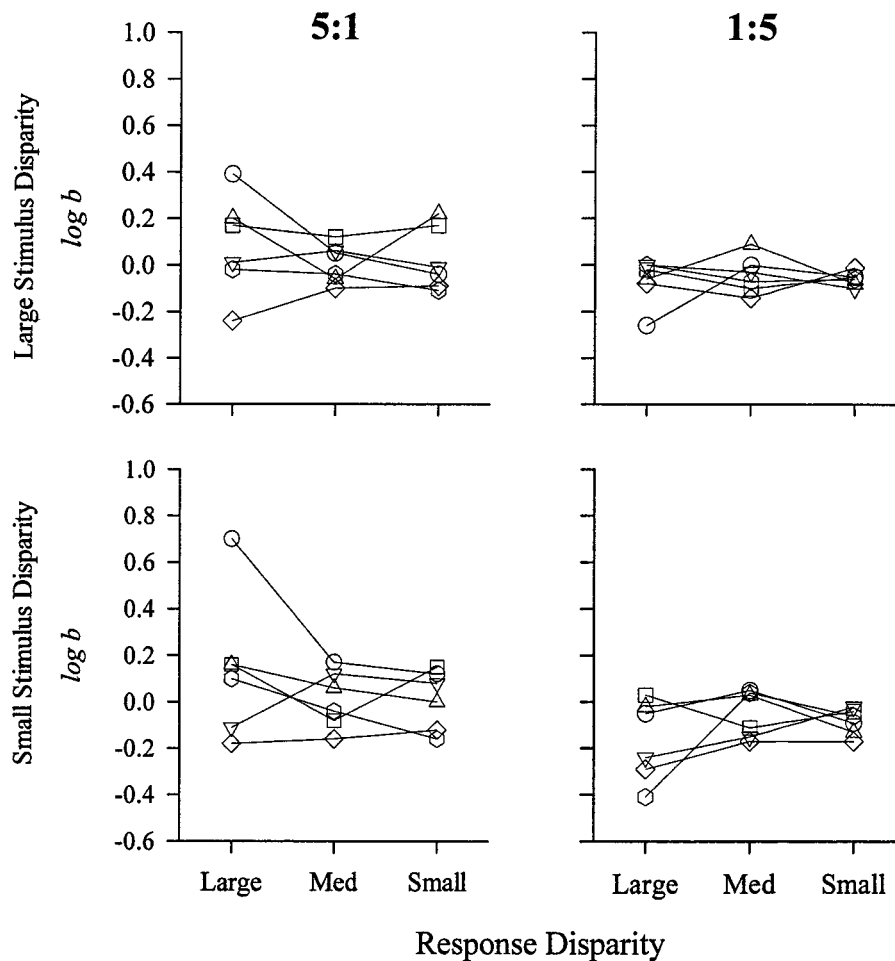


Fig. 2. Point estimates of response bias ($\log b$) for each participant as a function of response disparity for the large stimulus-disparity condition (upper panels) and the small stimulus-disparity condition (lower panels) of Experiment 1. Estimates from the 5:1 and 1:5 reinforcer-ratio conditions are plotted in the left and right panels, respectively.

sop, Rowley, & Fon, 1995; Johnstone & Alsop, 1996, 2000).

One major difference between the current study and previous experiments (Alsop et al., 1995; Johnstone & Alsop, 1996, 2000) concerns the manipulation of both sample-stimulus and choice-stimulus disparity. It is possible that the response-disparity manipulation rendered participants incapable of discriminating which of the two responses led to the more frequent delivery of reinforcement. Although the choice stimuli were different enough to allow accurate responding at all but the least disparate level of response disparity, the biasing effects of differential reinforcement might be more sensitive to changes in response disparity than discriminative

responding. Experiment 2 addressed this question by replicating Experiment 1 using greater response disparities.

EXPERIMENT 2

METHOD

Participants

Twelve undergraduate psychology students (7 female and 7 male), different from those in Experiment 1, participated for partial course credit. Ages ranged from 18 to 33 years, with a mean age of 19.9 years.

Apparatus and Stimuli

The apparatus and stimuli used were identical to those used in Experiment 1, with the

exception of the number of dots present in the response stimuli. In the large response-disparity condition, a B_1 choice stimulus contained 100 elements and a B_2 choice stimulus contained 80 elements. The B_1 and B_2 choice stimuli at the medium level of response disparity contained 98 and 82 dots, respectively. For the small response-disparity condition, a B_1 choice stimulus contained 96 dots and a B_2 choice stimulus contained 84 dots. The values for the small response-disparity condition were the same as those used for the large response-disparity condition of Experiment 1 (see Table 1).

Procedure

The design, instructions to participants, order of conditions and counterbalancing were identical to that of Experiment 1.

RESULTS AND DISCUSSION

As in Experiment 1, the number of B_1 and B_2 responses following each stimulus type were recorded, as were the number of reinforcers received for the two types of responses. The controlled-reinforcement procedure ensured that the log obtained reinforcer distribution (average = 0.70) was again similar to the arranged log reinforcer distribution (Appendix B). The same criteria regarding exclusion of trials as Experiment 1 were applied; that is, the first 72 trials at each level of stimulus and response disparity were removed, as were trials of latency less than 100 ms. Only one trial was under this latency criterion, and trials on which responses did not occur within 2,500 ms accounted for less than 1% of the data. Stability was assessed in the same manner as Experiment 1, and again no significant differences in summary estimates from the last two blocks of trials at each level of stimulus disparity were revealed. The collapsed data used in subsequent analyses are presented in Appendix B. Estimates of log d and log b were calculated using Equations 1 and 2 (see Experiment 1).

Discrimination

Figure 3 plots discrimination (log d) as a function of response disparity for both large and small stimulus disparities. The pattern of results was somewhat more variable than in the previous experiment; however, there were

no systematic differences in performance between reinforcer-ratio groups.

Discrimination tended to be lowest when response disparity was small. When the stimulus disparity was large, 4 participants in the 5:1 group showed monotonically decreasing trends in discrimination with decreased response disparity. For the 1:5 group, although only 2 participants showed monotonically decreasing trends, a further 3 participants showed consistent decreases in discrimination between the medium and small levels of response disparity. Overall, there was a significant decreasing trend in discrimination as response disparity decreased when evaluated using nonparametric trend analysis ($\Sigma S = 22$, $z = 3.05$, $p < .05$). When the stimulus disparity was small, there were less consistent effects of response disparity on discrimination, with only 1 participant in each group showing monotonically decreasing trends. Consequently, there was no significant trend at this level of stimulus disparity. The level of stimulus disparity influenced estimates of discrimination, with log d values larger in the large stimulus-disparity condition than in the small stimulus-disparity condition for each level of response disparity. The presence of higher discrimination with large stimulus disparity was confirmed by Wilcoxon matched-pairs signed-ranks tests at the large ($T = 1$, $p < .05$), medium ($T = 0$, $p < .05$), and small ($T = 5$, $p < .05$) levels of response disparity.

Bias

Estimates of bias are plotted in Figure 4 in the same manner as the discrimination data (Figure 3). Control by the asymmetric ratios of reinforcement appears to have been established, particularly at large response disparities. When response disparity was large, all 6 participants in the 5:1 group produced estimates of bias that were greater than 0 at both levels of stimulus disparity. Likewise, 5 participants in the 1:5 group exhibited bias estimates of less than 0 when response disparity was large at both levels of stimulus disparity. The majority of participants continued to exhibit biases in the direction predicted by the reinforcer ratio at the medium level of response disparity. Overall, estimates of bias tended to become less extreme as response disparity decreased, for both large and small stimulus disparities. Three participants in the

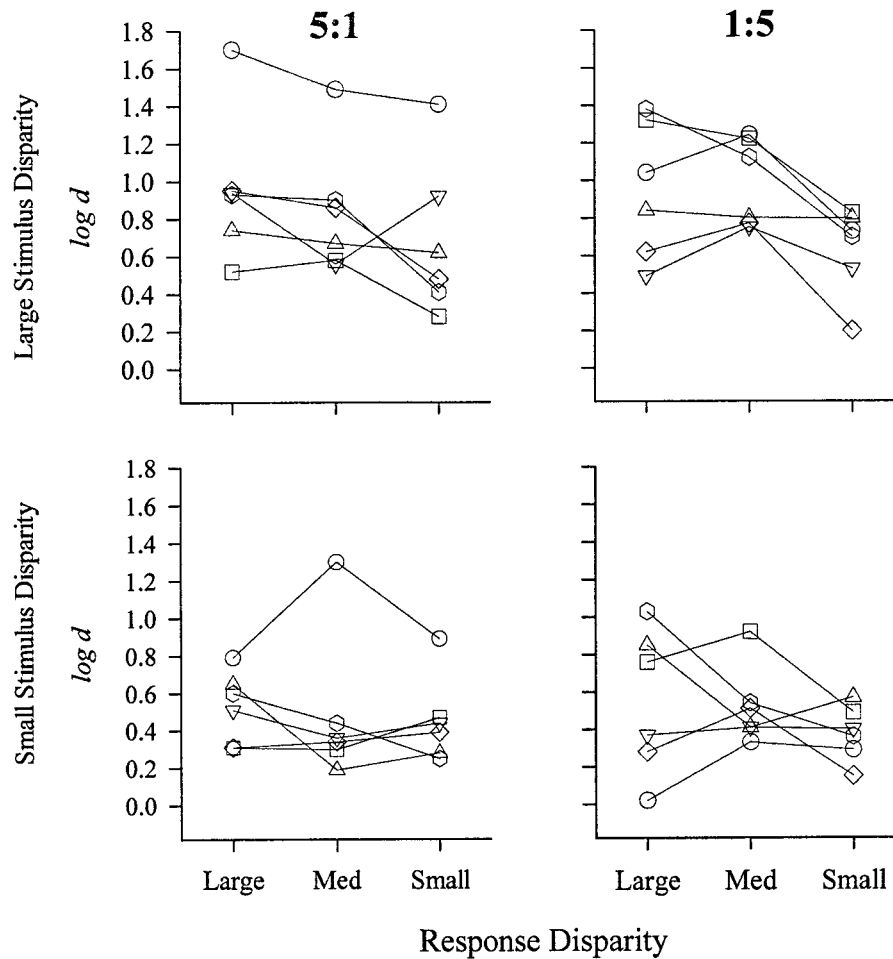


Fig. 3. Point estimates of discrimination ($\log d$) for each participant as a function of response disparity for the large stimulus-disparity condition (upper panels) and the small stimulus-disparity condition (lower panels) of Experiment 2. Estimates from the 5:1 and 1:5 reinforcer-ratio conditions are plotted in the left and right panels, respectively.

5:1 group showed monotonically decreasing trends as response disparity decreased at both levels of stimulus disparity. Response bias decreased between either the large and medium response-disparity levels or the medium and small response-disparity levels for a further 2 participants when stimulus disparity was large and for a further 3 participants when stimulus disparity was small. For the 1:5 group, 2 participants showed monotonically increasing trends when the stimulus disparity was large, and 3 participants showed this relation when the stimulus disparity was small. Estimates of response bias increased between either the large and medium response-disparity levels or the medium and small levels of response disparity for a further 3 partici-

pants when stimulus disparity was large and for an additional 2 participants when stimulus disparity was small. These trends were evaluated by first multiplying the estimates from the 1:5 group by -1 so that positive estimates from both groups reflect a preference for the most frequently reinforced alternative, and then conducting nonparametric trend tests on the combined data. Nonparametric trend tests revealed significant trends when the stimulus disparity was large ($\Sigma S = 12$, $z = 1.70$, $p < .05$) and when the stimulus disparity was small ($\Sigma S = 16$, $z = 2.26$, $p < .05$). Finally, estimates of bias for the two stimulus-disparity conditions did not differ at each level of response disparity when compared using Wilcoxon matched-pairs signed-ranks tests.

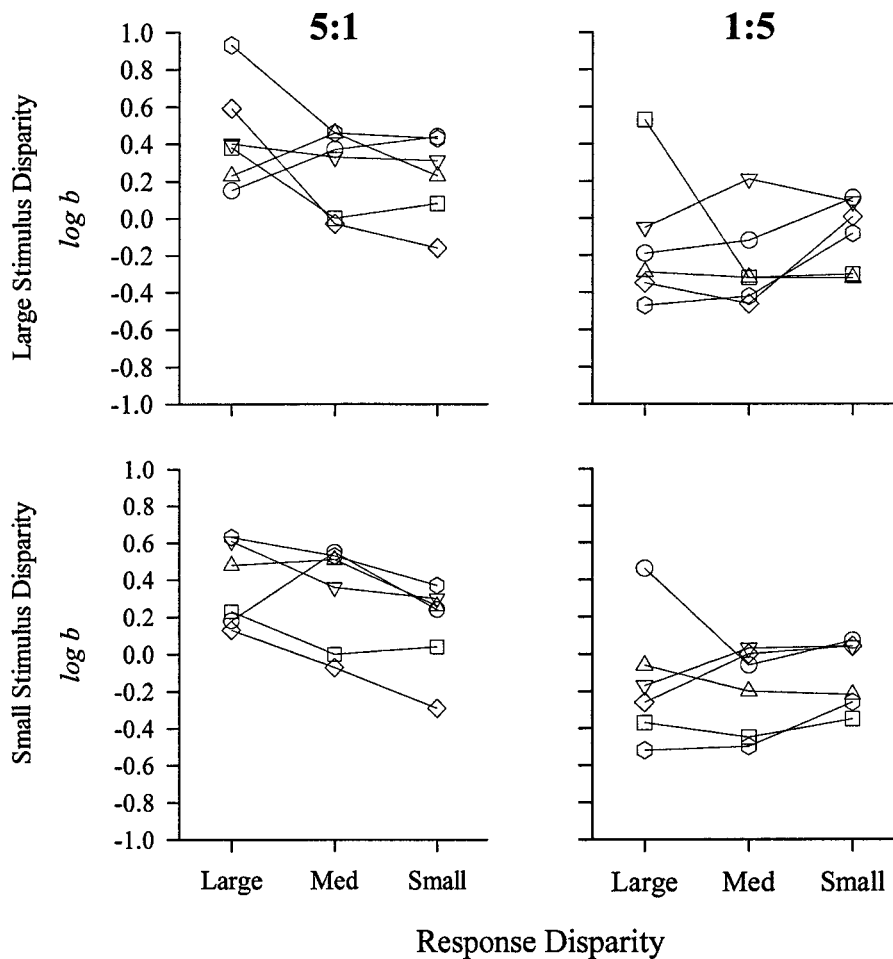


Fig. 4. Point estimates of response bias ($\log b$) for each participant as a function of response disparity for the large stimulus-disparity condition (upper panels) and the small stimulus-disparity condition (lower panels) of Experiment 2. Estimates from the 5:1 and 1:5 reinforcer-ratio conditions are plotted in the left and right panels, respectively.

The findings of Experiment 2 largely confirm that the response confusability manipulation influenced both discrimination and response bias. The decrease in measured bias as response disparity decreased confirms that the failure to observe an effect of response disparity on bias in Experiment 1 was due to the overall level of response disparity being too difficult for adequate differential reinforcer control to be achieved. This is also apparent in the overall larger estimates of response bias in Experiment 2, relative to Experiment 1.

GENERAL DISCUSSION

Taken together, the results of the present experiments provide further evidence for

conceptualizing detection tasks as discriminated operants, where stimulus, response, and reinforcer characteristics jointly determine performance (Davison & Nevin, 1999). Human performance on these tasks, like that of pigeons, involves a series of discriminations of which the disparity between the sample stimuli themselves are only one part. A complete model of detection performance must therefore capture the effects of stimulus, response, and reinforcer characteristics.

Experiments 1 and 2 showed that response-disparity manipulations in human detection produce effects similar to those seen with nonhuman animals. The results are consistent with two important features of the data of Nevin et al. (1993) and Godfrey and Dav-

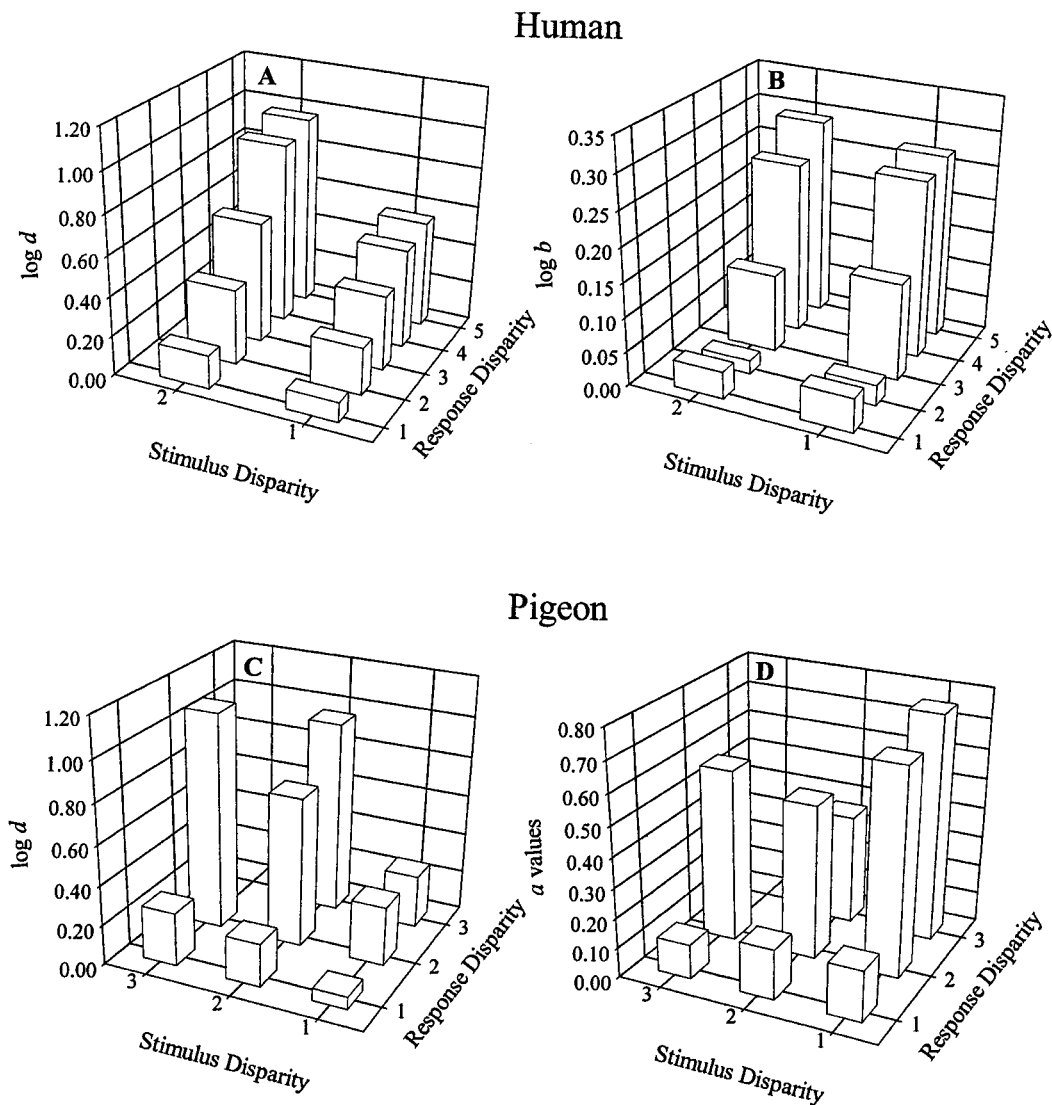


Fig. 5. The upper panels plot mean estimates of $\log d$ (Panel A) and $\log b$ (Panel B) for human participants from Experiments 1 and 2 as a function of stimulus disparity and response disparity. The lower panels plot estimates of $\log d$ (Panel C) and a (Panel D) for pigeon subjects from Godfrey (1997) and Godfrey and Davison (1998). For both stimulus and response disparity, 1 indicates the lowest level of disparity arranged. Note that there are no data for the most extreme response disparity at the most extreme stimulus disparity in Panels C and D, because this condition was not conducted.

ison (1998). First, decreasing response disparity usually resulted in lower estimates of discrimination (Figures 1 and 3). Second, decreasing response disparity reduced estimates of response bias, provided the overall level of response disparity was sufficient for reinforcement-based biases to occur (Figure 4).

The independent effects of stimulus disparity and response disparity in the current

experiments can be summarized with three-dimensional plots. Panels A and B of Figure 5 plot the data from Experiments 1 and 2 in this manner, averaged across all participants. In Figure 5, the different levels of stimulus disparity and response disparity are represented ordinally, with greater numbers indicating greater disparity. The data from the large response-disparity condition of Experi-

ment 1 and the small response-disparity condition of Experiment 2 were averaged, because they shared the same difference in the number of dots between the two choice stimuli. Panels C and D of Figure 5 present average data from Godfrey and Davison (1998) and Godfrey (1997), reanalyzed using the Davison and Tustin (1978) model of detection to allow comparison of corresponding pigeon data with the experiments reported here. The data from these studies are the most appropriate for comparison because similar stimuli were used to signal responses (dot density), and response disparity was manipulated in the same way as in the current experiments. Sensitivity to reinforcement (a), plotted in Panel D, can be considered as a measure of reinforcer control that is independent of inherent bias (c) (Davison & Tustin, 1978). The a parameter indexes the slope of the function relating the behavior ratio to the reinforcer ratio.

Figure 5 (Panels A and C) shows that the independent effects of stimulus-disparity and response-disparity manipulations on discrimination are similar for pigeon and human performance. Discrimination is highest when both stimulus and response disparity are highest, and is lowest when both stimulus and response disparity are lowest. Average estimates of discrimination are lower overall in the small stimulus-disparity condition than in the large stimulus-disparity condition, and reducing response disparity produces orderly decreases in discrimination at both levels of stimulus disparity.

Panel B presents estimates of bias from Experiments 1 and 2. The highest average estimates of bias were obtained when response disparity was highest, and decreasing response disparity produced orderly decreases in bias until the second-least disparate level of response disparity, at which point there appears to be a floor effect. There was no evidence of systematic changes in bias with stimulus-disparity manipulations, however; that is, at each level of response disparity, estimates of bias were similar for the two stimulus-disparity conditions. This appears to be inconsistent with previous reports of increases in sensitivity to reinforcement as stimulus disparity is reduced (e.g., Godfrey & Davison, 1998; Nevin et al., 1993). This interpretation of the $\log b$ data, however, must be treated

with caution because point estimates of $\log b$ include the influence of inherent biases, whereas previous research has measured sensitivity to reinforcement independently of inherent bias. It is possible that idiosyncratic inherent biases are obscuring changes in the degree of reinforcer-based bias as a function of stimulus disparity. That said, response disparity did influence average estimates of $\log b$ in Figure 5 (Panel B), and counterbalancing of the choice-stimulus location within a participant and the reinforcer ratio between participants should have attenuated any systematic inherent biases.

The ambiguity concerning the relation between stimulus disparity and estimates of response bias in the current data is perhaps not surprising. Previous research has provided less consistent evidence of this relation than other aspects of performance in these tasks. Nevin et al. (1993) showed increases in measures of reinforcer control when stimulus disparity was reduced, but McCarthy and Davison (1980) reported no increase in sensitivity to reinforcement with changes in stimulus disparity. The data provided by Alsop and Davison (1991) show both increases and decreases in reinforcer sensitivity as stimulus disparity is manipulated. Godfrey (1997) and Godfrey and Davison (1998) provide one of the most extensive data sets addressing this issue. Their reanalyzed data are plotted in Figure 5 (Panel D). In this analysis, sensitivity to reinforcement (a) usually decreased as response disparity was reduced, with the exception of the medium level of stimulus disparity, which increased from the highest level of response disparity to the medium level but then decreased from this level to the smallest level of response disparity. Overall, this aspect of their results is consistent with the bias estimates from human participants in the present study.

Together, however, Godfrey's (1997) and Godfrey and Davison's (1998) results show less clear evidence for increases in reinforcer sensitivity with decreases in stimulus disparity in this analysis. In some cases, values of a decreased or remained stable as stimulus disparity was decreased. Furthermore, the magnitude of the changes associated with manipulating stimulus disparity was relatively small in comparison with the effect of such manipulations on discrimination (Panel C).

Although changes in stimulus disparity might have influenced sensitivity to reinforcement in Godfrey's data, the effects were less orderly and the degree of influence was small relative to the effects on discrimination. When viewed in relation to these previous studies, the data from the current experiments do not seem too discrepant.

There is an interesting relation between discrimination and bias in the current experiments (Figure 5, Panels A and B). Some conditions that produced near-zero estimates of bias in the presence of an asymmetric reinforcer distribution were associated with above-zero estimates of discrimination, suggesting that stimulus control was present when control by the different reinforcer frequencies was very low or absent. In behavioral detection research, it is a commonly held view that there can be no stimulus control without some form of differential reinforcer control (e.g., Davison & Nevin, 1999), in the sense that differential responding under the two stimulus conditions is precluded if there is no discernible contingency between the two types of correct response and their associated reinforcement.

There are two obvious approaches to the possibility that reinforcer control, in the sense of maintaining accurate responding, remained in the absence of reinforcer control in terms of biased responding attributable to the asymmetric frequencies of reinforcement (Figure 5, Panel B). First, it might be that a certain level of disparity in the choice stimuli is sufficient for the subject to discriminate that responses following a given stimulus are reinforced on one alternative and never reinforced on the other alternative, but is insufficient for clear discrimination of the differences between the reinforcer *rates* of the two classes of correct response. Although this is the simplest interpretation of the data, it should be treated cautiously because no behavioral model of detection distinguishes between these two types of reinforcer control.

The second approach reflects a difference between the procedure used with pigeons and that used here with human participants. In the current experiments, the participants received instructions defining accurate responding. These instructions might have had some role in maintaining accurate responding in the absence of any differential control

relating to the asymmetric reinforcer frequencies. It is clear that verbal instructions can influence humans' behavior in operant tasks (e.g., Baron & Galizio, 1983). We cannot distinguish between the influences of instructional and reinforcer control in the current task, because both would maintain accurate responding. In the current case, however, it is still true that a certain level of response disparity was sufficient to allow accurate responding but was insufficient to show the biasing effects of different frequencies of reinforcement, even though this latter effect was easily obtained at large response disparities. Future extensions of behavioral models of detection to procedures with humans might need to address the relative contribution of instructions and reinforcement contingencies.

Although the relation between stimulus control and reinforcer control in the current experiments is equivocal, it raises an interesting general issue regarding the nature of reinforcer control in these tasks. Reinforcer control in a detection task can be conceptualized on at least three levels. In its broadest sense, reinforcer control reflects the strength of the relation between schedules of reinforcement and the likelihood of a response. For example, in single-schedule research (e.g., Herrnstein, 1961), reinforcer control is seen in changes in response rate with changes in the frequency of reinforcement. Such control maintains any behavior on the task. At another level, differential reinforcement maintains accurate responding in two-alternative detection tasks because reinforcement is scheduled only for the responses designated correct for each stimulus condition (but see Davison & McCarthy, 1980; Nevin, Jenkins, Whittaker, & Yarensky, 1982; Nevin, Olson, Mandell, & Yarensky, 1975). Reinforcer control in this sense is implicit in accurate discriminative responding in two-alternative tasks. Finally, differential reinforcer control can produce response biases when the distribution of reinforcement across two alternatives is asymmetric because of differences in magnitude, delay, or frequency of reinforcement. This is the type of reinforcer control indexed by the bias and sensitivity-to-reinforcement parameters of Davison and Tustin's (1978) model. The data from the current experiments with humans suggest that at certain levels of response disparity, accurate

responding occurred even when there was little evidence of bias due to differential reinforcement. One interpretation of this finding is that the bias parameters provided by the Davison–Tustin model do not capture all aspects of reinforcer control, although these parameters are frequently referred to in that manner (e.g., McCarthy & Davison, 1991). The notion that reinforcer control may be present when the biasing effects of asymmetric reinforcement are not exhibited, and the definition of reinforcer control in terms of models of detection, remain interesting conceptual issues.

The present studies support previous research (e.g., Alsop, 1991; Alsop & Davison, 1991; Davison, 1991; Davison & Nevin, 1999; McCarthy & Davison, 1991) showing that the relation between measures of discrimination and response bias is more complicated than that captured by models such as Davison and Tustin's (1978) account or more traditional signal-detection approaches (e.g., Green & Swets, 1966). A formal analysis of the present results by more recent behavioral approaches to detection (e.g., Alsop & Davison, 1991; Davison & Nevin, 1999) was not possible in this case, however. These models have the disadvantage of requiring experiments with a greater number of reinforcer-ratio manipulations to obtain accurate parameter estimates. The use of human participants constrained the number of conditions that we could reasonably expect our participants to complete.

The practical constraints associated with the use of humans raise some other issues. First, the combined analysis of Experiments 1 and 2 presented in Figure 5 used data from two different groups of participants. No single participant was exposed to all five levels of response disparity plotted in this figure, so the continuous function is a composite of two groups of participants. That said, it is important to note that the only unusual finding, namely, the lack of an effect of stimulus disparity on response bias, is always based on a within-participant comparison. Second, the differential ratio of reinforcement was manipulated between participants, so that one group received more frequent reinforcement for B_1 responses and a second group received more frequent reinforcement for B_2 responses. Finally, only two levels of stimulus disparity

were employed, which prevents a thorough investigation of the relation between stimulus disparity and reinforcer control. However, the difference between the two levels of disparity was sufficient to show marked differences in discrimination. Despite these methodological differences between the current human experiments and research with pigeons, the data from these experiments were remarkably consistent with the data from Godfrey (1997) and Godfrey and Davison (1998). Nevertheless, the issues raised here may help to explain the failure to find a systematic effect of stimulus disparity on estimates of bias and reconcile the differences between these data and those of other studies (e.g., Nevin et al., 1993).

Alsop (1998) noted that contemporary reviews of detection performance (e.g., Macmillan & Creelman, 1991; Swets, 1986) tend to overlook the substantial body of research generated in the experimental analysis of behavior. In part, this seems to arise because nonhuman animals are typically used as subjects in this field. The present experiments demonstrated that comparable results can be obtained with humans using procedures analogous to those used with nonhuman animals. In this particular case, the comparison concerns the role of response disparity on detection performance. More generally, these results suggest that conceptualizing detection as discriminated operants (e.g., Alsop, 1998; Davison & Nevin, 1999; Nevin et al., 1993) may be beneficial in more traditional experimental and applied uses of detection theory. Such an approach provides a more complete picture of the factors that influence performance, and this allows these factors, once identified, to be controlled to reduce variance in measures and to engineer environments that maximize performance.

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APPENDIX A

The number of responses emitted following S_1 (B_{11} and B_{12}) and following S_2 (B_{21} and B_{22}) stimulus presentations, and the number of reinforcers obtained for correct responses (R_{11} and R_{22}) for each participant in each condition of Experiment 1. Data are from the last 144 trials of each stimulus-disparity condition.

Partici- pant	Stimulus disparity	Response disparity	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}
1	Large	Large	68	4	19	53	60	11
		Medium	58	14	17	55	47	11
		Small	39	33	30	42	34	7
	Small	Large	65	7	52	19	38	8
		Medium	48	24	38	34	39	8
		Small	41	31	41	31	27	5
2	Large	Large	57	15	26	45	51	11
		Medium	61	11	17	55	55	11
		Small	53	19	32	40	45	9
	Small	Large	48	23	36	36	36	6
		Medium	51	21	16	56	47	8
		Small	43	29	41	31	35	7
3	Large	Large	58	14	27	45	43	9
		Medium	48	24	20	52	44	8
		Small	47	25	43	29	38	7
	Small	Large	51	21	33	39	35	8
		Medium	48	24	29	43	40	9
		Small	47	25	25	47	44	10
4	Large	Large	62	9	9	59	55	10
		Medium	49	19	24	47	38	8
		Small	45	25	24	46	34	6
	Small	Large	50	22	15	57	42	9
		Medium	48	22	29	37	40	7
		Small	41	27	34	35	38	8
5	Large	Large	58	13	5	66	54	11
		Medium	42	25	19	51	42	9
		Small	38	31	25	46	37	6
	Small	Large	45	27	15	57	39	7
		Medium	33	34	23	47	30	6
		Small	32	38	27	40	30	4
6	Large	Large	45	19	18	47	38	9
		Medium	46	20	17	48	36	6
		Small	35	37	28	43	31	6
	Small	Large	57	15	21	50	50	9
		Medium	46	26	23	48	36	8
		Small	33	38	25	46	28	5
7	Large	Large	47	25	10	62	10	51
		Medium	53	18	18	53	10	47
		Small	40	24	22	47	7	39
	Small	Large	49	20	17	53	9	46
		Medium	50	21	25	47	8	41
		Small	34	33	27	43	9	36
8	Large	Large	50	22	20	51	8	49
		Medium	46	26	19	53	8	40
		Small	41	31	27	45	8	37
	Small	Large	42	29	31	40	6	35
		Medium	42	30	22	50	7	38
		Small	34	38	34	36	5	27
9	Large	Large	58	14	11	61	11	54
		Medium	56	16	22	50	10	48
		Small	45	27	21	51	8	42
	Small	Large	57	15	14	58	9	49
		Medium	44	28	30	41	7	37
		Small	38	34	24	48	6	42

APPENDIX A

(Continued)

Partici- pant	Stimulus disparity	Response disparity	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}
10	Large	Large	50	22	22	50	9	46
		Medium	34	38	35	36	6	33
		Small	37	35	27	45	7	38
	Small	Large	32	40	21	51	7	38
		Medium	33	39	27	45	8	36
		Small	38	34	32	40	7	35
11	Large	Large	43	29	23	49	8	41
		Medium	38	34	23	49	8	43
		Small	38	34	33	39	6	38
	Small	Large	32	40	18	54	7	41
		Medium	39	33	20	52	8	43
		Small	33	39	25	46	8	42
12	Large	Large	61	11	11	61	12	59
		Medium	44	16	14	53	9	43
		Small	37	27	22	39	7	36
	Small	Large	42	30	7	65	9	48
		Medium	49	21	24	47	8	38
		Small	36	25	22	41	7	32

APPENDIX B

The number of responses emitted following S_1 (B_{11} and B_{12}) and following S_2 (B_{21} and B_{22}) stimulus presentations, and the number of reinforcers obtained for correct responses (R_{11} and R_{22}) for each participant in each condition of Experiment 2. Data are from the last 144 trials of each stimulus-disparity condition.

Partici- pant	Stimulus disparity	Response disparity	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}
1	Large	Large	71	1	2	70	66	14
		Medium	72	1	5	67	57	12
		Small	70	1	7	65	54	12
	Small	Large	65	7	14	58	59	11
		Medium	71	1	11	61	63	12
		Small	67	5	13	59	56	11
2	Large	Large	64	8	30	41	54	10
		Medium	57	15	15	57	49	11
		Small	50	22	28	44	39	6
	Small	Large	55	16	32	38	42	9
		Medium	48	24	24	48	42	9
		Small	55	17	19	52	43	8
3	Large	Large	65	7	17	55	55	10
		Medium	67	5	27	44	52	10
		Small	63	9	21	51	55	10
	Small	Large	67	5	29	43	61	12
		Medium	60	12	49	23	39	8
		Small	56	16	35	37	49	10
4	Large	Large	65	3	16	55	52	11
		Medium	62	8	27	45	49	10
		Small	68	4	14	58	61	13
	Small	Large	65	5	35	28	48	10
		Medium	59	11	34	34	46	9
		Small	61	11	30	41	48	9
5	Large	Large	69	2	22	50	60	10
		Medium	61	9	8	63	50	10
		Small	44	21	12	52	38	8
	Small	Large	52	19	28	43	48	10
		Medium	47	25	20	52	44	10
		Small	39	31	12	57	38	6
6	Large	Large	71	1	36	36	62	10
		Medium	69	3	19	53	58	10
		Small	63	9	37	35	49	10
	Small	Large	68	4	37	35	46	11
		Medium	65	7	40	32	51	9
		Small	58	14	41	31	43	9
7	Large	Large	63	9	4	68	11	61
		Medium	67	5	3	69	12	58
		Small	63	9	14	58	11	52
	Small	Large	54	18	53	19	4	19
		Medium	47	25	21	51	10	47
		Small	50	22	27	45	8	37
8	Large	Large	71	1	10	62	9	47
		Medium	64	8	2	70	12	57
		Small	55	16	5	67	12	56
	Small	Large	51	21	5	67	11	60
		Medium	53	18	3	69	13	54
		Small	42	30	9	62	9	45
9	Large	Large	56	16	5	67	12	57
		Medium	54	18	5	67	12	56
		Small	54	18	5	67	10	53
	Small	Large	62	10	8	64	13	55
		Medium	44	27	14	57	9	47
		Small	49	22	10	61	12	51

APPENDIX B

(Continued)

Partici- pant	Stimulus disparity	Response disparity	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}
10	Large	Large	53	19	16	56	9	47
		Medium	64	7	16	56	9	47
		Small	58	14	19	53	9	41
	Small	Large	44	28	16	55	8	41
		Medium	53	19	21	50	9	43
		Small	53	19	22	50	9	44
11	Large	Large	47	25	7	65	10	48
		Medium	48	24	4	68	11	51
		Small	48	24	32	40	7	32
	Small	Large	37	35	16	56	9	46
		Medium	55	17	17	55	10	45
		Small	44	28	31	40	6	32
12	Large	Large	64	8	1	71	14	65
		Medium	60	12	2	70	12	54
		Small	58	14	10	61	13	52
	Small	Large	55	17	2	70	12	57
		Medium	37	34	6	66	9	46
		Small	40	32	14	58	10	47